School of Finance

University of St.Gallen

EXTREME SPILLOVER BETWEEN SHADOW BANKING AND REGULAR BANKING

FLORENTINA PARASCHIV
MINZI QIN

WORKING PAPERS ON FINANCE NO. 2013/12

INSTITUTE OF OPERATIONS RESEARCH AND COMPUTATIONAL FINANCE (IOR/CF – HSG)

JULY 2013

EXTREME SPILLOVER BETWEEN SHADOW BANKING AND REGULAR BANKING

Florentina Paraschiv[1]

University of St. Gallen, Institute for Operations Research and Computational Finance, Bodanstr. 6, CH-9000, St. Gallen, Switzerland, email: florentina.paraschiv@unisg.ch

Minzi Qin

University of St. Gallen, minziqin.s@gmail.com

Abstract

The current financial crisis brought light to a large banking sector that existed for decades within the "darkness" of the financial system - the shadow banking sector. Shadow bank assets are widely traded in the financial markets and shadow banking activities are intertwined with the daily business of regular banks. This unregulated banking sector has become systematically important. Its failure affected the entire banking system. We present a model based on multivariate extreme value theory, which allows us to measure crashes and liquidity squeezes. Using the stable tail dependence structure, we measure the interdependency between the tail probabilities of the regular banking sector and the shadow banking sector. This allows us to calculate the conditional spillover likelihood between asset returns and liquidity spreads for selected crash levels. The empirical results indicate a fairly strong contagion probability between shadow bank assets and regular bank assets.

[1] Corresponding author: Florentina Paraschiv

1. Introduction

1.1 Problem Identification

The U.S. subprime financial crisis can be viewed as a result of long-term unlimited expansion of credit. The shadow banking system is the main tool for credit expansion. It is a new financial structure which creates liquidity with high efficiency. This new *banking* system is able to turn market liquidity into bank liquidity through innovative financial products. It maximizes the profit of financial institutions by offering them the possibility to increase their liquidity.

On the one hand, shadow banking creates conditions for the conversion and aggregation of liquidities. This kind of high-risk operation system is an underlying danger for the sudden interruption and collapse of the entire financial system, as it was the case during the recent subprime financial crisis. During periods of economic boom, these risks are less obvious because investors are confident and willing to provide investments. However, during economic downturns, these hidden risks will be exposed and indefinitely enlarged (Yi & Wang, 2010. p. 5-7). Regarding the recent economic crisis, this resulted in the collapse of, first, the shadow banking system and then the large U.S. investment banks. The insolvency of highly leveraged institutions followed, money markets were in panic, and redemption of thousands of highly leveraged hedge funds finally led to the worldwide financial crisis (Gorton, 2008, p. 24-26).

When reviewing the financial crisis, the close relationship between regular banking and shadow banking sectors cannot be overlooked. Hence, the scope of systemic risk in the financial markets, considering this unregulated banking sector, became a highly relevant topic. Especially the issue on how to model such systemic risk which moved to the top of regulators' and risk managers' to-do lists.

1.2 Objective

This paper will primarily give insight into the subprime crisis vis-à-vis one of its main catalysts: the shadow banking system. It will first describe this system, keeping a focus on the framework of shadow banking as well as its relation to regular banking. This should lead to a better understanding of the subprime mortgage crash and the liquidity panic that affected the entire regular banking sector. Furthermore, we will look empirically at the asset price crash and liquidity squeeze and determine the spillover effect from shadow banks to the regular banks as well as to the whole economy. We identify the systemic risk between the shadow banking sector and the regular banking sector. In addition to banks that were closely related to shadow banks, we will also consider banks within the regular banking sector that had minimal or no exposure to the shadow banking assets as well as some non-financial institutions. We intend to find out whether the crash of shadow banking sector has the same contagion effect on different sectors of the economy. In order to capture extreme events like the crisis, we will consider the extreme value theory for the spillover estimator.

2. Literature overview

Although the financial crisis took place five years ago, its impact on the economy is still present. The amount of literature dealing with this topic increases significantly, tackling the crisis problem from different perspectives. Most of these sources mainly focus on the regulatory point of view, financial derivatives or global imbalances. There is rather little literature that has empirically measured the risk of shadow banking system. This is rather mainly due to the limited availability of data sources.

Adrian, Ashcraft, Boesky and Pozsar (2010) described the characteristics, the business model, the activities, the product of a shadow bank and its relation to the regular banks. Also Gennaioli, Shleifer and Vishny (2011) presented a model of shadow banking. The paper firstly denotes the securitization of financial intermediaries, in which they originate and trade loans, then construct the loans into diversified portfolios and use the riskless debt to fund these portfolios. The model argues that the securitization only allows banks to diversify idiosyncratic risk but concentrating their exposure to systematic risk. Shadow banks themselves would become especially fragile when tail risk is neglected. Similar findings can be found as well in Tian (2010), Hsu and Moroz (2010) or Nersisyan and Wray (2010).

Acharya, Schnabl and Suarez (2011) analyzed asset-backed commercial paper (ABCP) conduits and its role in the early phase of the financial crisis of 2007-2009. The paper especially intensified that the main motivation of commercial banks for setting up a conduit and performing securitization is to gain on the regulatory arbitrage. The paper showed that conduits were unable to transfer risk and losses outside the banks during the “run” and were responsible for the lower stock returns of the banks. Covitz, Liang and Suarez (2012) also have reviewed the collapse of the ABCP market during the financial crisis and found out that the run on ABCP programs were related to program-level and macro-financial risks. By looking at the breakdown in the arbitrage foundation of the ABX.HE indices (derivatives linked to the underlying subprime bonds) during the panic, Gorton (2009) could indirectly explain the influence of an illiquid repo market on the shadow banks.

Adrian and Ashcraft (2012), Adrian and Shin (2009), Financial Stability Board 2011, Gorton and Metrick (2009), Ricks (2010), Tarullo (2012) have highlighted the exigency to regulate also the shadow banks. They pointed out that according to shadow banks size in the financial markets and its importance to the whole economy, regulatory board can no longer ignore this “too systematically important to fail” part of financial markets. In their paper, different regulation possibilities have been suggested from a theoretical as well as from a practical point of view.

From the literature we get a very comprehensive understanding about shadow banking itself, its contribution to the crisis, its connection to the traditional banking system. Nevertheless a big part of shadow banks and their activities still remain vague and the focus of literature stays rather theoretical. Due to this opacity, shadow banks can only rarely be studied empirically.

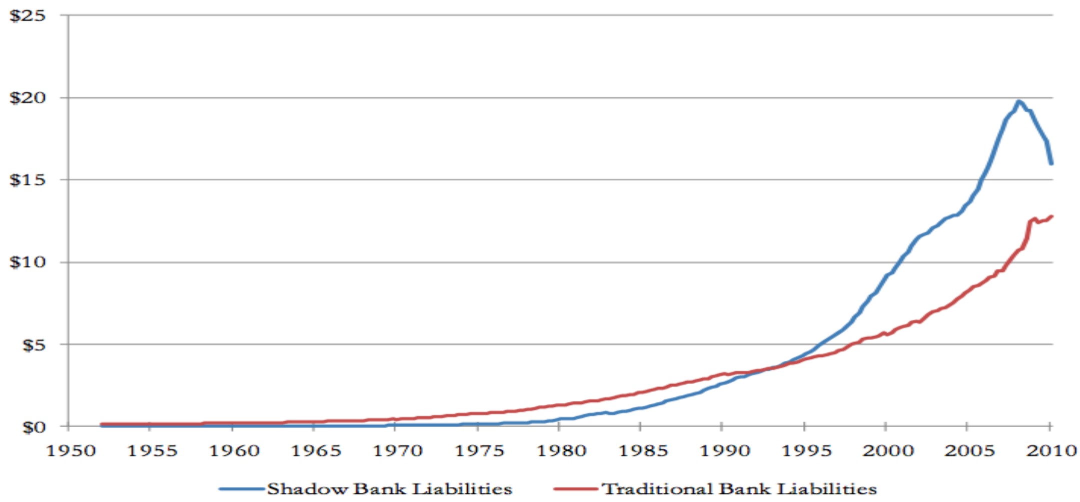
Recently, numerous authors have investigated the spillover measurement in the financial markets, and various methods and models have been used for the spillover estimation. Cheung et al. (2010) considered Granger-causality test in the mean processes of asset returns to measure the shock spillover effect between U.S. and foreign markets. Longstaff (2010) empirically estimated the contagion effect of the price of subprime asset-backed collateralized debt obligation to other markets. The estimation method of the paper was based on the value at risk. Brunnermeier and Pedersen (2009) described the liquidity shock contagion effect by linking the market liquidity of assets and funding liquidity for traders together. Kyle and Xiong (2001) described financial contagion effect in a continuous-time model. By using a time-varying liquidity premia model, Vayanos (2004) stated that if liquidity shock goes from one market to another market, the contagion would occur.

3. Shadow banking system

With the financial globalization and the deregulation in several countries, the global financial system has undergone a significant change in the recent 20 to 30 years. Due to junk bonds and commercial papers on the one hand, and the money-market mutual funds on the other hand, bank balance sheets endured a strong pressure and traditional banks became less profitable. This trend shifted the traditional banking business model remarkably towards a new financing technique - the shadow banking business model. It switched from a traditional financing model made up of credits and loans to a new financing model: the debt financing model (Ojo, 2010, p. 17). Shadow banks relied heavily on the debt financing technique, which seems to have high profitability. The required funds come directly from the stock market through securitization instead of personal saving. In that sense it is still a credit relation, but hidden behind securitization.

The main advantage of debt financing is to facilitate the conversion of liquidity or the liquidity creation (Yi & Wang, 2010. p. 5-7). The intensive shadow-banking rise in the recent years is especially due to the liquidity creation characteristic: First, derivatives traded within shadow banks enable credit institutions to achieve liquidity. In addition, the derivatives provide the possibility to access a wide range of financial investors (Ojo, 2010, p. 18). Then, shadow banking systems are able to turn illiquid assets with long maturities such as mortgage into liquid assets such as mortgage backed securities (MBS) (Tian, 2010, p.10). During the last decades the shadow banking system has grown rapidly and intensively to a large and important part of the financial system. With the expansion of public and private market participants, the system has grown to a size of nearly 20 trillion USD in March 2008, which exceeds significantly the liabilities of the traditional banking system (Adrian et al., 2010, p. 11).

Figure 1: Shadow Bank Liabilities vs. Traditional Bank Liabilities, $ trillion



Source: Shadow Banking (Adrian et al., 2010)

The significant rise of shadow banking also indicates that the focus of risk management should be relocated; the credit risk management no longer covers the risk faced by a bank in its daily operations (Yi & Wang, 2010, p. 12).

4. Methodology

Liquidity crisis is defined as a sudden and prolonged evaporation of both market and funding liquidity, with potentially serious consequences for the stability of the financial system and the real economy. In the recent financial crisis, both market- and funding liquidity risk occurred at the same time, which did freeze the national and international financial markets. This paper will measure the market- and liquidity risks of different shadow banking assets and banks exposed to those assets by looking at co-crash probabilities. For assessing market risk we take the returns of the considered financial institutions. For practical purposes we will model liquidity risk with bid-ask spreads. Yakov (1986) established the dependency between asset pricing and bid-ask spreads. It allows us to assume that liquidity can be approximated through bid-ask spreads, where high liquidity coincide with a low bid-ask spreads and vice versa.

Following the approach of Embrechts, Klüppelberg, & Mikosch (1997) and Embrechts, Frey and McNeil (2005) we employ the extreme value theory (EVT) to model extreme events in our returns and liquidity spreads. We further apply the model developed by Straetmans (2000) to estimate the probability of co-crashes in a certain sample period.

4.1 Extreme Value Theory (EVT)

As historically evident, extreme events have an enormous impact on the global economy, eg the 1980 Latin America debt crisis, 1987 the Black Monday (the largest one-day percentage decline in stock market history), 1992-1993 the Black Wednesday-speculative attacks on currencies in the European exchange rate mechanism, 1994-1995 economic crisis in Mexico (speculative attack and default on Mexican debt), 1997-1998 Asian financial crisis (devaluations and banking crisis across Asia), 1998 Russian Financial crisis, 2001 bursting of dot-com bubble (speculations concerning internet companies crashed) and finally the 2007-2009 financial crisis. Hence, how to manage such severe events caught the attention of managers and regulators. Indeed each party wants to reduce its losses due to the extreme event, without giving up upside in the "good times". As standard models based upon a normal framework or regulator specifications, eg Basel II and Basel III, were not sufficient, more sophisticated models had to be developed.

With extreme value theory (EVT), distributions that correctly reflect the frequency of such events have been introduced and accordingly estimators have been developed to fit the historical data to those distributions.

EVT can be used to model the distribution of excess loss over a certain threshold (eg maximum loss). One of the most prominent distributional models which considers the exceedance over thresholds is the Generalized Pareto distribution (GPD), which is given by McNeil, (1999, p. 4-7):

$$G_{\xi,\beta(u)}(X) = \begin{pmatrix} 1-\left(1+\frac{\xi X}{\beta}\right)^{-\frac{1}{\xi}} & if \quad \xi \neq 0 \\ 1-e^{-\frac{X}{\beta}} & if \quad \xi = 0 \end{pmatrix}$$

Given the distribution function F of the random variable X, which denotes in this case the loss, the excess distribution of X over the threshold u is given by:

$$F_u(x) = P(X-u \leq x | X > u) = \frac{F(x+u)-F(u)}{1-F(u)}$$

for $0 \leq x < xF - u$, where $xF \leq \infty$ is the right endpoint of F. Here u indicates the threshold and F_u represents the distribution of excesses of X over this threshold u. This excess distribution F_u can perfectly model the extreme tails of a loss function. With the progressively rising u, the excess distribution F_u converges to a generalized Pareto. Then for a given threshold u and u large enough, we can approximate F_u by the following GPD:

$$F_u(X) \approx G_{\xi,\beta(u)}(X), u \to \infty, X \geq 0$$

where $\beta > 0$, and $X \geq 0$ when $\xi \geq 0$ and $0 \leq X \leq -\frac{\beta}{\xi}$ when $\xi < 0$. ξ denotes the tail index and β refers to the parameter scale. When $\xi > 0$ the distribution is called an ordinary Pareto distribution with $\alpha = \frac{1}{\xi}$ and $\kappa = \frac{\beta}{\xi}$.

We employ Hill's estimator for the Pareto distribution. Based on the observations $X_1, X_2, \dots X_n$ Hill's estimator is given by

$$(\hat{\alpha}_{k,n}^{H})^{-1} = \frac{1}{k}\sum_{i=1}^{k} \log \frac{X_{n-i+1,n}}{X_{n-k,n}}$$

where k denotes the highest order statistics used in the estimation. The highest order statistics k should be chosen in such a way that the Mean Square Error of the estimator is minimized. This means we wish to reduce the squared bias and the variance of the estimator at the same rate with increasing sample size. In practice we will plot Hill's estimator for different levels of k and try to find a threshold over which the estimator is relatively constant.

Our goal is to evaluate the risk of extreme events while employing a standard Value at Risk (VaR) framework. It has been shown that for EVT distributions with tail index greater than 1 the sub-additivity condition is satisfied and hence VaR is also coherent. For a proof we refer to Danielsson, Jorgensen, Samorodnitsky, Sarma and Vries (2011). As Value at Risk is more popular and requires less data for the estimation (Yamai & Toshinao 2005), we will use this risk measure for our empirical analysis. Accordingly to Embrechts et al. (2005) the probability that $F(X)$ might fall below a certain level is given by the Value at Risk:

$$VaR_\alpha(X_i) = -\inf\{x \in R | F(X_i \leq x) \leq 1 - \alpha\}$$

But not only the univariate case is of importance, we also want to know if crises tend to spread or are isolated. Hence we want to know to which extent financial markets are interconnected and the probability of co-movements during times of extreme financial stress.

4.2 Bivariate Extreme Value Theory

Bivariate EVT provides knowledge about the dependence structure in the joint tail of the distribution. In other words, it tells us about joint loss/crash probability. It is to note that bivariate EVT does not provide an explicit parametric form for the tail dependence function.

Copulas[2] provide us information about the joint distribution of standard uniform random variables. With copulas the dependence structure of a set of random variables can be characterized separately from the marginal distribution:

$$C(U, \dots, V) = p\{U \leq u, \dots, V \leq v\}$$

with $0 \leq u \leq 1,\ 0 \leq v \leq 1$.

In the bivariate case we consider random variables $X_1, \dots, X_n, Y_1, \dots, Y_n$, with joint distribution function F:

$$F(x, y)^n = p\ \{X_n \leq x, Y_n \leq y\}$$

and continuous marginal distribution functions $F_{i,}\ i = X, Y$. The copula function C (the dependence structure) can be defined as:

$$C(u, v) = F\left(F_X^{-1}(u), F_Y^{-1}(v)\right)$$

where $F_X^{-1} and\ F_Y^{-1}$ are the quantile functions, which are defined as: $(F_X^{-1}(u) = \inf\{x: F_X(x) \geq u\}$ and $F_Y^{-1}(v) = \inf\{y: F_Y(y) \geq v\})$.

4.3 The Extremal Spillovers

Based on the paper of Straetmans (2000), the following part will provide an introduction of how to measure the spillover effect from a theoretical point of view. The emphasis lies especially on the spillovers in the financial markets during the

[2]For a definition we refer to Embrechts et al. p. 184

extreme events. The spillover model that is applied in Straetmans' paper considers a semi-parametric approach based upon the EVT, which has been introduced in the previous section. The spillover risk refers to the risk of contagion, which could happen between similar markets, segments, investment portfolios and so on. Asset prices can either crash simultaneously or one asset X crashes given another Y crashes first. It is to point out that we define the crash of an asset as when the price of that asset drops below the predefined lowest acceptance level (let's say *x* or *y*), ie a certain threshold.

The likelihood that two assets, ie X and Y may crash simultaneously given that at least one assets (X or Y) falls below the critical level can be defined as follows:

$$p\{\kappa = 2 | \kappa \geq 1\} = \frac{p_1 + p_2}{p_{12}} - 1$$

with

$$p_1 = p\{X > x\},$$

$$p_2 = p\{Y > y\}$$

$$p_{12} = p\{X > x \; or \; Y > y\}$$

where κ denotes the number of assets indices that crash simultaneously for κ= 0,1,2. The returns and spillover measurement will be mapped into the first quadrant. This definition of simultaneous crash also considers the negative extremal spillovers between the assets, however the minus signs need to be set correctly.

As already mentioned above, the spillover risk can also refer to the probability that one asset crashes given that another asset crashes first:

$$p\{Y > y | X > x\} = \frac{p_1 + p_2 - p_{12}}{p_1} - 1$$

and

$$p\{X > x | Y > y\} = \frac{p_1 + p_2 - p_{12}}{p_2} - 1$$

For the integration of extreme value theory into these spillover measures we refer to Streatmans (2000). Consistent with his approach we estimate the univariate tail probabilities of the single assets p_1 and p_2 and the bivariate tail probability between two assets p_{12}.

5. Data Description

In our analysis we consider historical total return time series as well as liquidity spreads, which we obtained from Bloomberg. Four different asset pools were derived: "S*hadow banks basket", "Banks with large shadow bank assets exposure basket",* "*Banks with small/non shadow bank assets exposure basket*" and "*Non-financial institutions basket*". In order to avoid the country specific characteristics like different stock listing rules, different currencies etc. we will only analyze the financial institutions in the United States. However our study can easily be extended to an international framework.

For shadow bank time series we mainly focus on asset-backed securities, which are the most traded and repacked instruments in the financial markets (Gorton & Metrick, 2010, p. 11-16). A list of asset-backed securities funds was published on Bloomberg under market data; we considered our shadow assets from this list in our analysis.

From the banking side, for "Banks with large shadow bank assets exposure basket" we firstly went through the shadow banking asset list from Bloomberg and tried to find the direct relation between shadow banking assets and regular bank assets. We analyzed the annual reports of individual banks in order to look at their direct exposure to shadow banking assets, ie which and how many shadow assets are exposed by which banks. However, banks do not list their "shadow activities", eg off-balance sheet activities in details, and we were only able to view the aggregated information. Hence, we had to consider other criterion to select our data group in this basket. We considered investment and commercial banks in this data basket and excluded retail banks. Investment banks and commercial banks conduct much of their business with the shadow banking system. Retailer banks with traditional business are rather less involved with the shadow banking activity, eg securitization. Hence, off-balance sheet securitization, off-balance sheet credit default swap and contingent liability support and SIVs sponsoring (or ABCP conduit) in the annual reports of banks was our most important selection criterion. In addition as the balance sheets illustrate, banks that belong to this basket have low liquidity ratio and high leverage ratios. Large parts of their liabilities are short-term debts. For retail banks, the liabilities are rather long term. Also we considered the performance of each bank during the financial crisis. We assume banks with large shadow assets exposure had strong financial difficulties, eg a significant return drop and liquidity spread increase during the crisis.

For *"Banks with small/non shadow bank assets exposure basket"* we consider the rather regional banks, which are mainly retail banking. Retail banks mainly focus on traditional banking business, ie credit intermediation. Funding of retail banks comes mostly from long-term deposits, which are rather stable due to deposit insurance and having central banks as lender of last resort. This type of bank is less vulnerable to a run. Retail banks do not sponsor any SIVs and have barely off-balance sheet activities. The performance of these banking groups was quite stable during the crisis.

Finally for "Non-financial institution basket" we randomly pick large companies from the S&P 500, which are non-financial institutions. We mainly consider pharmacy, medical and energy companies.

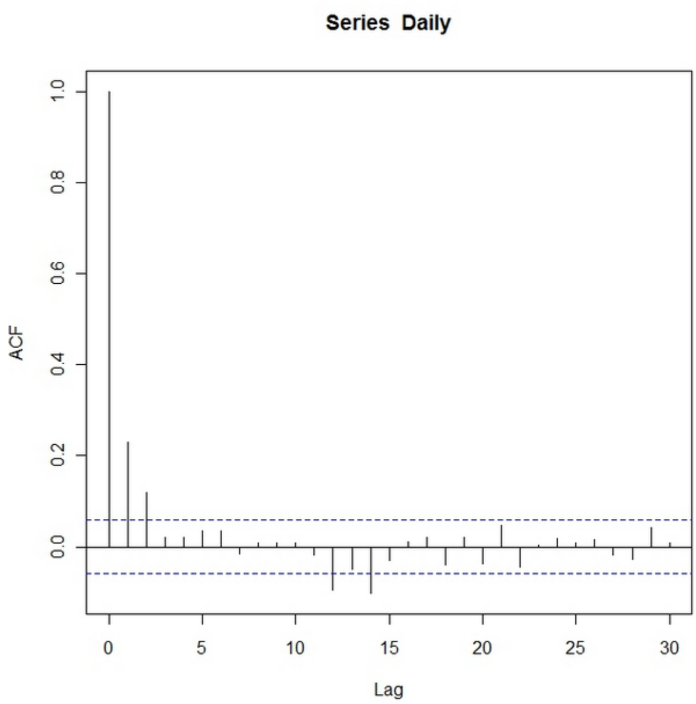
We select for each basket three to five representatives. In the descriptive statistics table we clearly show which financial or non-financial institutions enter our different baskets. We choose weekly total return time series that run from 17th November 2003 to 7th January 2013. In this case we can completely capture the extreme events. We have firstly analyzed individually the four groups of assembled data baskets. We derived descriptive statistics by computing the mean and standard derivation, the gain and the drop during the financial crisis, sharp ratio and draw down expressed in volatility. Results can be found in Table 1. We selected out of each basket a sub-set of representative data which best characterizes our baskets. For each basket we consider institutions with respectively low, middle and high draw down expressed in volatility. Especially for *Banks with large shadow bank assets exposure basket* we deliberately select the investment banks Goldman Sachs, MerillLynch, MorganStanly, JP Morgan to characterize this basket. Accordingly to Journal of Credit Risk these investment banks have had the most subprime exposure[3]. Moreover these large investment banks have had extreme difficulties during the crisis.

Table 1: Descriptive statistics

Shadow Banks		Mean	SD	Gain	Drop	Sharp Ratio	Draw Down Expressed in Vola
HRT	Helios Total Return Fund	0.12%	2.67%	21.37%	-16.93%	0.05	-6.334
MRF	American Income Fund Inc.	0.15%	1.77%	8.91%	-7.42%	0.08	-4.181
FMY	Fist Trust Mortgage Income Fund	0.16%	2.13%	15.46%	-16.52%	0.07	-7.752
MTGDX	Morgan Stanley Mortgage Securities I	0.08%	0.98%	13.28%	-11.85%	0.08	-12.134
Bank With Large Shadow Assets Exposure		**Mean**	**SD**	**Gain**	**Drop**	**Sharp Ratio**	**Draw Down Expressed in Vola**
FULT	Fulton Financial Corporation	0.11%	4.56%	22.59%	-24.75%	0.02	-5.433
Goldman	Goldman Sachs	0.16%	4.54%	19.64%	-15.91%	0.03	-3.502
MerrilLynch	MerrilLynch	0.12%	1.14%	3.94%	-8.44%	0.10	-7.416
MorganSt	Morgan Stanly	0.10%	2.73%	16.57%	-18.09%	0.04	-6.632
JP	JPMorgan	0.22%	4.39%	25.81%	-17.16%	0.05	-3.907
Bank With Less/No Shadow Assets Exposure		**Mean**	**SD**	**Gain**	**Drop**	**Sharp Ratio**	**Draw Down Expressed in Vola**
BBT	BB&T Financial FSB	0.06%	4.42%	20.83%	-19.35%	0.01	-4.378
HTLF	Heartland Financial USA Inc.	0.19%	5.08%	18.79%	-14.13%	0.04	-2.780
NBT	NBT Bancorp, Inc.	0.18%	4.35%	27.40%	-15.58%	0.04	-3.581
Non Financial Company		**Mean**	**SD**	**Gain**	**Drop**	**Sharp Ratio**	**Draw Down Expressed in Vola**
ABT	Abbott Laboratories	0.17%	2.60%	9.06%	-19.97%	0.06	-7.673
ABC	AmerisourceBergen Corporation	0.18%	3.34%	11.47%	-24.82%	0.05	-7.420
NS	NuStar Energy L.P.	0.19%	2.92%	16.42%	-8.60%	0.06	-2.941

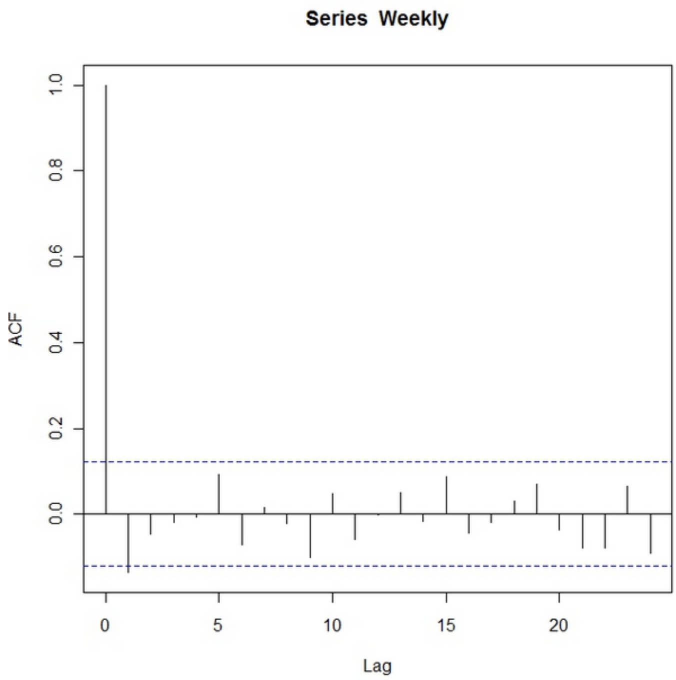
We consider weekly data in order to reduce the autocorrelation between the data points. (This is a requirement to apply our theoretical framework correctly). Monthly data may reduce autocorrelation even more, but at this level we would not have sufficient data points for a meaningful empirical analysis.

Figure 2: Autocorrelation function of asset exposed to shadow banks (daily returns)



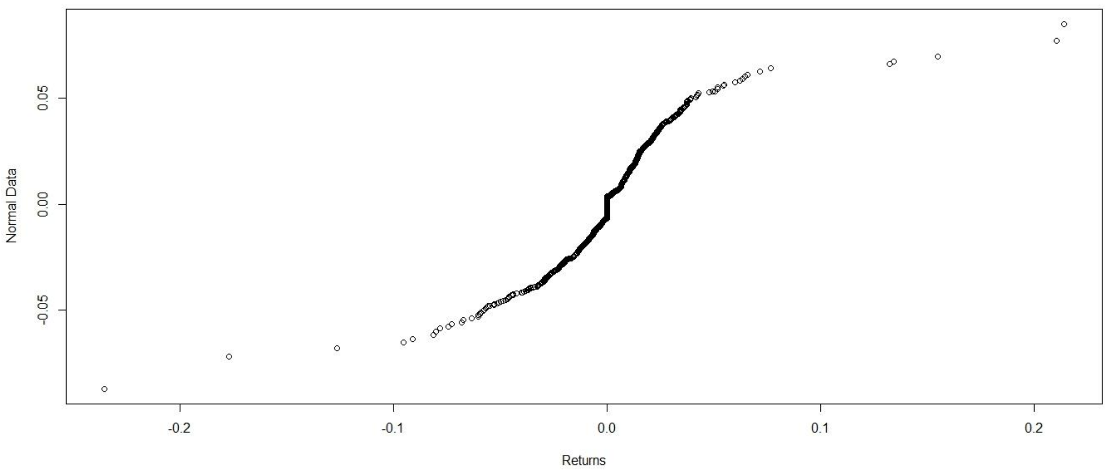
[3]The Journal of Credit Risk, Vol. 5/Nr.2., 2009.

Figure 3: Autocorrelation function of asset exposed to shadow banks[4] (weekly returns)



Before starting with the estimation process and fitting our data into the estimators, we want to verify if our data exhibit fat tails. Only in this case, we feel confident in using the extremal spillover model that applies a bivariate extreme value framework. The Q-Q plot confirmed our assumption that our data are not normally distributed. Figure 4 was reproduced for each asset.

Figure 4: Q-Q plot for HTR, as shadow bank asset proxy vs a normal distribution



[4] UBS 2008-2013

Next we have to specify our calibration of the Hill estimator. As described in the theoretical parts, for the computation of the Hill estimator we should select the *k* in a way that the bias-squared and variance vanish at the same rate with the increasing sample size *n*. Therefore the ratio $\frac{k}{n}$ is critical for the resulting $\hat{\alpha}^{H}_{k,n}$. We have computed Hill plots for all our time series and select the level of *k* in the region where $\hat{\alpha}^{H}_{k,n}$ can be viewed as more or less constant. In Figures 5-12 we plot Hill estimates regarding *k* for the total returns and liquidity spreads of the four baskets.

Figure 5: Hill plot return for HTR

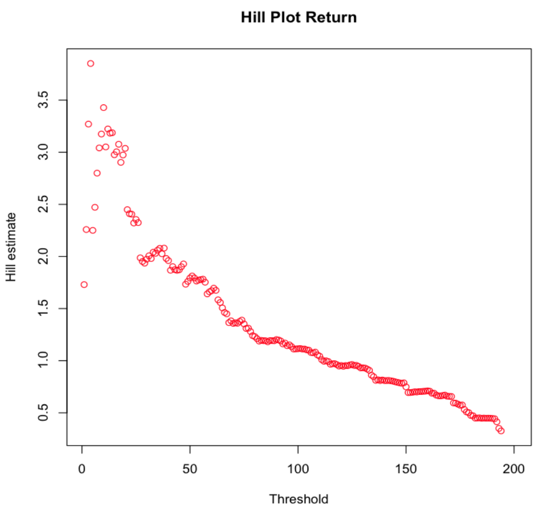


Figure 6: Hill plot spread for HTR

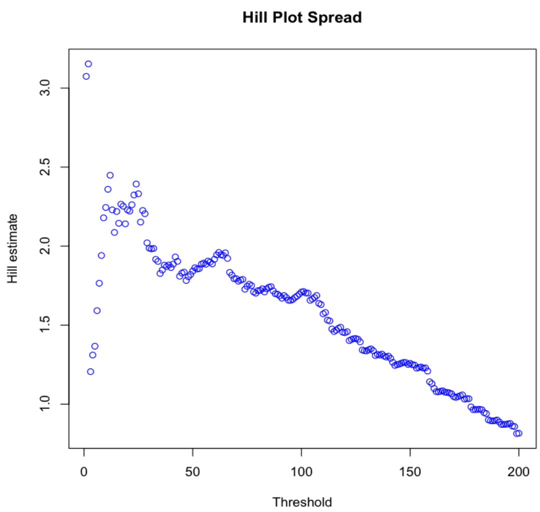


Figure 7: Hill plot return for Morgan Stanley

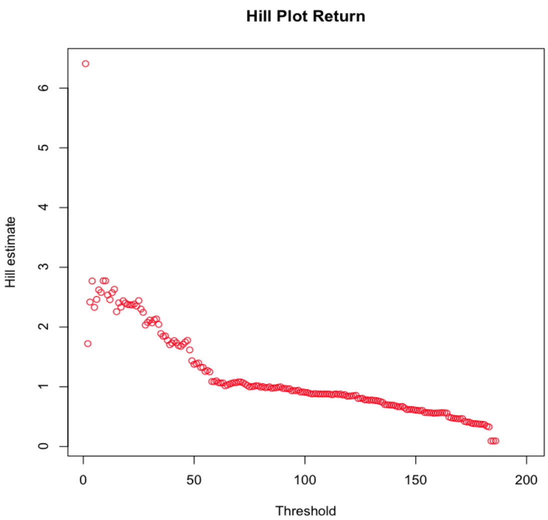


Figure 8: Hill plot spread for Morgan Stanley

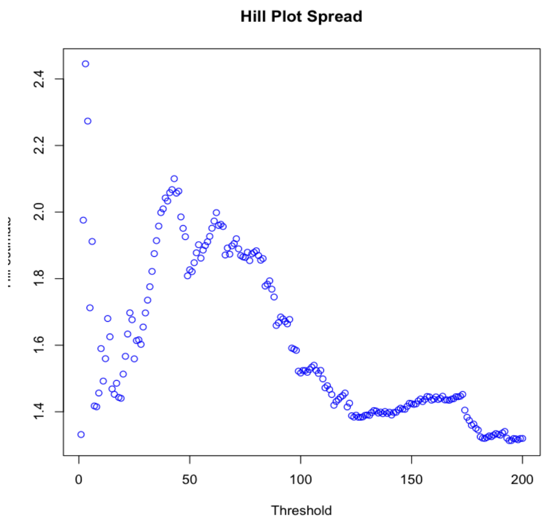


Figure 9: Hill Plot Return for BBT

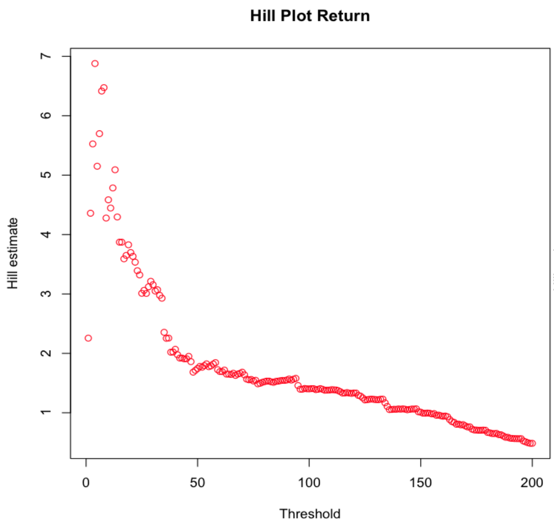


Figure 10: Hill plot spread for BBT

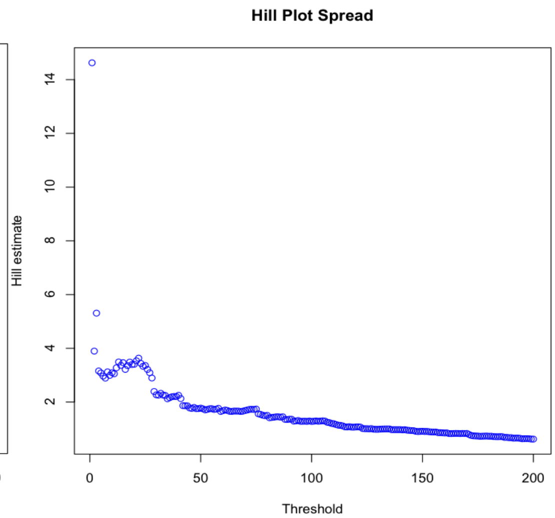


Figure 11: Hill plot return for BBT

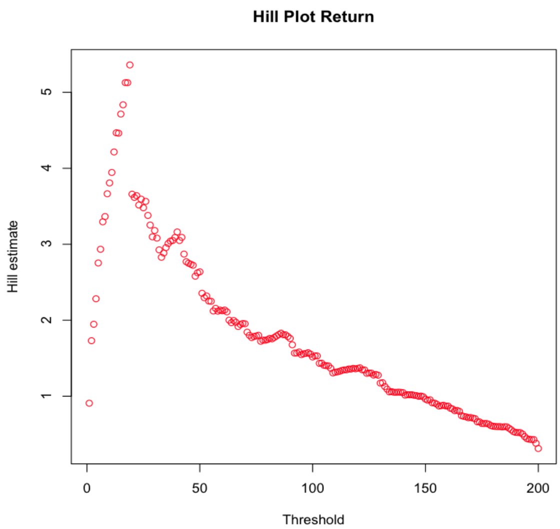
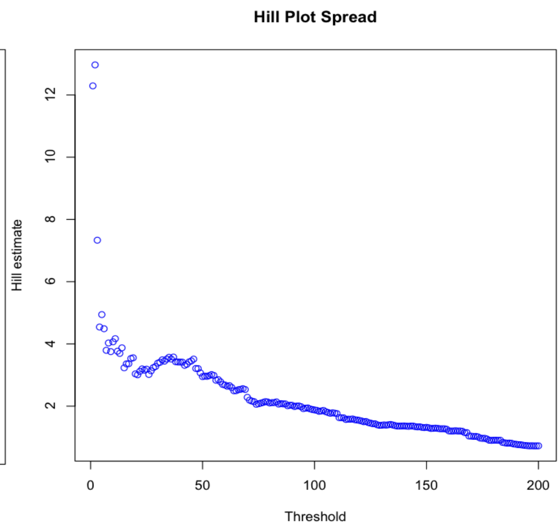


Figure 12: Hill plot spread for BBT



From the Hill plots we could observe that each individual return and spread has different horizontal range for the estimated tail index. However we are able to observe trends from returns and spreads. For returns an optimal threshold value lies mostly between 50 and 120 and for spreads an optimal threshold value lies between 50 and 150. For the given size of 445 weekly returns and spreads, we choose k=50 for returns and k=60 for the spreads.

6. Empirical Results

6.1 Value at Risk Analysis

We will firstly present a value at risk analysis for the different assets. In Table 2 we summarized the expected maximum loss over the selected time horizon, eg 10 years within 99.9% confidence level. We calculated VaR for our data considering both normal and extreme distribution assumption. In the second and third column we presented the VaR of returns for each financial institution. Comparing column two that takes extreme events into account with column three that considers only normal market behavior, the incurred loss in column two is far heavier than the loss illustrated in column three. Hence, we can observe that the VaR with normal distribution assumption totally underestimated the underlying risk during systemic events. Therefore in order to capture the potential loss that might occur during extreme stress situation, EVT is clearly the better approach to consider.

Table 2: EVT- and Normal VaR (Returns)

Financial Institutions	Return $VaR_{\_EVT}$	Return $VaR_{\_Normal}$
HTR	0.3629	0.0361
MRF	0.3059	0.2064
FMY	0.1472	0.0293
ML	0.0502	0.0150
JP	0.5856	0.2864
GS	0.2597	0.0621

Confidence Level: 99.99%

6.2 Univariate Results

Table 3 displays tail index estimates, maximum return drop and univariate exceedance probabilities for weekly total time series of the financial institutions.

Table 3: Left tail probabilities for data baskets total returns

Shadow Banks	$\hat{\alpha}^{H}_{k,n}$	**Maximum Drop (%)**	**-10%**	**-20%**	**-30%**
HTR	2.229	-16.93	0.00482	0.00116	0.00042
FMY	1.827	-16.52	0.00591	0.00166	0.00079
MRF	2.530	-7.42	0.00292	0.00158	0.00077
MTGDX	2.436	-11.85	0.00111	0.00024	0.00020
Banks with Large Shadow Assets Exposure	$\hat{\alpha}^{H}_{k,n}$	**Maximum Drop (%)**	**-10%**	**-20%**	**-30%**
JP Morgan	2.505	-17.16	0.03375	0.01410	0.00847

Morgan Stanley	2.455	-44.72	0.01359	0.00551	0.00325
Merrill Lynch	3.170	-8.44	0.00697	0.00291	0.00174
FULT	2.753	-24.75	0.03242	0.01322	0.00783
Goldman	2.665	-15.91	0.02763	0.00836	0.00415
Banks with Low Shadow Assets Exposure	$\hat{\alpha}^H_{k,n}$	**Maximum Drop (%)**	**-10%**	**-20%**	**-30%**
BBT	3.404	-19.35	0.02215	0.00733	0.00357
NBT	2.807	-15.58	0.02877	0.01047	0.00578
HTLF	3.011	-14.13	0.03451	0.00668	0.00255
Non Financial Institutions	$\hat{\alpha}^H_{k,n}$	**Maximum Drop (%)**	**-10%**	**-20%**	**-30%**
ABT	2.987	19.97	0.03238	0.00041	0.00012
ABC	2.903	24.82	0.00543	0.00073	0.00223
NS	2.407	8.60	0.00726	0.00137	0.00052

The tail index estimates are displayed in column two and have been calculated by considering Hill's estimator with the chosen highest order statistic k. In the third column we display the maximum drop of the in-sample return. The value will be considered as an indicator for the out-of-sample threshold selection for the spillover measurement. Additionally we have calculated the probability of extreme events by assuming that the defined critical level will be exceeded from column four to six. We have defined three critical levels -10%, -20% and -30%, which illustrate the possible return drop per week.

The listed probabilities can be used as benchmark for the portfolio selection. It is important to precise that returns displayed in Table 3 are assumed to perform independently. That means no dependencies between asset price movements are considered here. With increasing tail dependencies between the assets, the probability of extreme events may also increase.

6.3 Multivariate Results

In Table 4 we reported the systemic risk estimation for pairs of assets of different financial institutions. In this table we will mainly present the spillover probability between shadow bank assets and assets of regular banks that are tightly interconnected with shadow banks. The estimated extremal spillovers in the table are assumed to have a common extreme quantile of 10%. Our decision to define the quantile at level 10% is based on the reported in-sample maxima return drops in

Table 1. Indeed most of the assets experienced in our sample at least once a return drop of more than 15% within a week.

The first column displays the name of the assets pairs. In the second column the estimated spillover measurement regarding systemic risk probabilities is presented, where the assets of two financial institutions are assumed to crash at the same time. The column three and four both deliver information about the alternative conditional spillover estimation, which means that a specified crash of one asset is required in advance.

Table 4: Estimated spillover probability across shadow banks (X) and regular banks with large shadow bank assets exposure (Y)

Total Returns (X-Y)	P {k=2| k ≥1}	P {Y > y| X > x)	P {X > x| Y > y)
HTR – Goldman	0.196	0.518	0.207
HTR - FULT	0.160	0.411	0.151
HTR - Merrill Lynch	0.020	0.020	0.144
HTR - Morgan Stanley	0.225	0.339	0.124
HTR - JP	0.189	0.389	0.110
MRF - Goldman	0.069	0.511	0.028
MRF - FULT	0.028	0.217	0.005
MRF - Merrill Lynch	0.032	0.033	0.098
MRF - Morgan Stanley	0.118	0.390	0.027
MRF - JP	0.092	0.469	0.002
MTGDX - Goldman	0.069	0.999	0.022
MTGDX - FULT	0.028	0.564	0.020
MTGDX - Merrill Lynch	0.032	0.024	0.065
MTGDX - Morgan Stanley	0.118	0.491	0.019
MTGDX - JP	0.092	0.335	0.025

Quantile equal x = y = 10%, where X refers to the return drop of shadow bank assets and Y refers the return drop of assets of regular banks with large shadow assets exposure

The last two columns of the table show conditional spillover probabilities which show the likelihood that the regular bank assets will crash if the shadow bank assets collapse. We are able to observe relatively high spillover probabilities in this case. Two third of the asset pairs contain a spillover likelihood around 40%.

Almost all the spillover probabilities reported in the fourth column are smaller than the ones reported in the third column. This is in our opinion reasonable, since during the recent crisis the crash started firstly with the subprime sector. As mentioned in the theoretical part, because the shadow-banking sector held the most subprime mortgage related instruments, the shadow bank assets were the first ones to crash. After the collapse of the shadow-banking sector, banks which had large exposure to the shadow banking assets started to suffer from the massive price drop and liquidity squeeze, however, with a time lag. Mortgage related shadow-banking assets are recorded in the SPVs where banks have guaranteed contingent liabilities. Only when SPVs started to have refinancing difficulties the banks will step in as parent company.

The implicit risk with which banks deal is actually very high. Compared to the rest of the spillover probabilities, the numbers denoted in the last column are smaller. This column illustrates the contagion probability, given that the regular banks assets crash, then the shadow bank assets will also crash. According to the fact that the shadow banks were the first ones who faced a crash and not the regular banks, we do not expect to observe a high contagion effect from regular banking sector to shadow banking sector. In addition, shadow banks provide no contingent liability guarantee to regular banks. In case regular banks would face a refinancing problem, the shadow banks are not obliged to bail out the regular banks.

Comparing the results from Table 4 to the univariate results displayed in Table 3, we can see that all probabilities increased remarkably. When we consider the extreme dependence structure between the assets, the probability of systemic risk will increase. This provides regulators and risk managers an important message, ie they should not look at the isolated market risks. The financial system becomes more and more interconnected and therefore it is worth to always look at the possible tail dependence probability. We also calculated the spillover probability for the liquidity spread. The results are displayed in Table 5.

Table 5: Estimated liquidity spreads spillover probability across shadow banks (X) and regular banks with large shadow bank assets exposure (Y)

Spreads (X-Y)	$P\{k=2 \mid k \geq 1\}$	$P\{Y > y \mid X > x)$	$P\{X > x \mid Y > y)$
HTR - Goldman	0.105	0.126	0.239
HTR - FULT	0.142	0.856	0.133
HTR - Merrill Lynch	0.148	0.152	0.074
HTR - Morgan Stanley	0.436	0.676	0.661
HTR - JP	0.178	0.797	0.214
MRF - Goldman	0.107	0.139	0.291
MRF - FULT	0.106	0.857	0.224
MRF - Merrill Lynch	0.031	0.984	0.187

MRF - Morgan Stanley	0.436	0.676	0.506
MRF - JP	0.171	0.797	0.208
FMY - Goldman	0.586	0.695	0.072
FMY - FULT	0.522	0.924	0.038
FMY - Merrill Lynch	0.047	0.048	0.023
FMY - Morgan Stanley	0.370	0.388	0.188
FMY - JP	0.596	0.994	0.063

Quantile equal x = y = 10%, where X refers to the spread increase of shadow bank assets and Y refers to the spread increase of assets of regular banks with large shadow assets exposure

The spillover probability indicates the same trends as in Table 4. The second column with simultaneous spillover probability shows a smaller value compared to the conditional spillover probability displayed in the fourth column. Also in Table 5, the last column has the smallest contagion likelihood. Therefore the explanation for the resulting probability values is identical to the previous section. Nevertheless, the probabilities we obtained here are much higher than the ones in Table 4. This is however not surprising. When liquidity froze in the shadow-banking sector, the regular banking sector also felt immediately the liquidity squeeze. Regular banks had to take back the illiquid securities onto their books and write these down. No one had any idea to what extend banks were exposed to the bad assets, investors were unwilling to provide further liquidity to the market and banks started to distrust mutually and stopped lending to each other. The mistrust accelerated the further price drop and increased Repo haircut. Liquidity quickly evaporated from the market and froze the transactions in the whole financial markets (Borio, 2009, p. 9). Liquidity spread got unusually high. Table 5 fairly sends out the message that banks with large shadow bank assets exposure are very sensitive to the liquidity status of the shadow bank assets. If we observe 10% liquidity spread increase in the shadow banking assets, with 60% probability regular banks will also face an increase of liquidity spread by 10%.

In general we are able to observe a rather high extreme dependency structure between the two components of the financial sector. The results show that the liquidity spread has a much higher contagion effect compared to the return drop. These numbers should provide regulator and risk managers interesting information regarding the potential vulnerability of the regular banks that have a tight relationship with the shadow-banking sector.

Now it is interesting to look at the contagion effect from shadow banks to regular banks that are barely exposed to shadow bank assets. The spillover probabilities displayed in Table 6 are on average, as expected, smaller than the probabilities illustrated in Table 4. Especially the conditional probability from the third column differs between the two tables, however not in an extremely large scale.

Table 6: Estimated return drop spillover probability across shadow banks (X) and regular banks with low shadow bank assets exposure (Y)

Total Returns (X-Y)	P {k=2 | k ≥1}	P {Y > y | X > x)	P {X > x | Y > y)
HTR - BBT	0.154	0.422	0.087
HTR - HTLF	0.135	0.425	0.060
HTR - NBT	0.213	0.390	0.137
MRF - BBT	0.040	0.301	0.014
MRF - HTLF	0.041	0.360	0.013
MRF - NBT	0.088	0.394	0.006
MTGDX - BBT	0.033	0.442	0.018
MTGDX - HTLF	0.012	0.195	0.010
MTGDX - NBT	0.034	0.273	0.016

Quantile equal x = y = 10%, where X refers to the return drop of shadow bank assets and Y refers to the return drop of assets of regular banks with low shadow bank assets exposure

The spillover likelihood in Table 6 lies around 25%, where the probability in Table 4 lies around 40%. Since the chosen regular banks do not trade intensively with shadow banks and provide no guarantees to SPVs, they are not really affected by the price crash of shadow banking assets. The observed contagion probability might not directly come from the shadow banking assets. We believe the price drop rather comes from the “domino” effect. Although the regular banks in this basket have in general low connections to shadow banks, they have a tight relationship with banks that have already undergone huge losses from the first waves of crisis. For example, through instruments like Repo the banking sector becomes one big network and is as well highly interconnected. The financial framework was in a critical condition during the time between middle 2008 and beginning of 2009. Asset prices dropped in large amounts, liquidity was practically frozen in the market and Repo margin went unreasonably high. During this time most of the banks had to suffer, regardless whether they are exposed to the shadow banking assets or not. Due to the fact that investors cannot distinguish which bank had actually shadow bank assets exposure, they generally stopped their investment in banking related instruments.

Furthermore the banks also lost trust among each other. Because they were not sure how many bad assets the other banks were holding on their balance sheet they stopped lending to each other. Hence, the regular banking sector, even with low shadow bank assets exposure, also starts to tremble after the crash of the shadow-banking sector.

Table 7: Estimated liquidity spread spillover probability across shadow banks (X) and regular banks with low shadow bank assets exposure (Y)

Spreads (X-Y)	P {k=2| k ≥1}	P {Y > y| X > x)	P {X > x| Y > y)
HTR - BBT	0.154	0.203	0.074
HTR - HTLF	0.095	0.712	0.998
HTR - NBT	0.151	0.917	0.880
MRF - BBT	0.154	0.203	0.073
MRF - HTLF	0.095	0.712	0.140
MRF - NBT	0.151	0.917	0.974
FMY - BBT	0.243	0.737	0.023
FMY - HTLF	0.001	0.001	0.061
FMY - NBT	0.001	0.001	0.043

Quantile equal x = y = 10%, where X refers to the spread increase of shadow bank assets and Y refers to the spread increase of assets of regular banks with low shadow bank assets exposure

The estimated liquidity spread spillover probabilities for banks with small shadow banking assets are displayed in Table 7. Liquidity spreads spillover probabilities also denote a higher value than the probabilities denoted in Table 5. We would give the same explanation as in the previous section. The liquidity squeeze comes from the regular banking market. Where the interbank loan on the one side required more and more risk premium, on the other side the collateral used for the interbank loan lost sharply on value and banks needed to provide additional collateral. During the crisis, liquidity shortage became a critical issue. In the end, market liquidity frosted and banks had extreme refinancing difficulties. Therefore the contagion effect of liquidity spread is stronger than the return crash. Finally, we investigate the estimated results between shadow banks and non-financial companies. In Table 8 we show the spillover probabilities of the asset crash of these two types of institutions.

Table 8: Estimated return drop spillover probability across shadow banks (X) and non-financial companies (Y)

Total Returns (X-Y)	P {k=2| k ≥1}	P {Y > y| X > x)	P {X > x| Y > y)
HTR - ABT	0.068	0.077	0.196
HTR - ABC	0.179	0.302	0.151

HTR - NS	0.135	0.425	0.204
MRF - ABT	0.156	0.226	0.018
MRF - ABC	0.091	0.348	0.032
MRF - NS	0.041	0.360	0.074
MTGDX - ABT	0.115	0.233	0.036
MTGDX - ABC	0.029	0.193	0.008
MTGDX - NS	0.012	0.195	0.025

Quantile equal x = y = 10%, where X refers to the return drop of shadow bank assets and Y refers the return drop of non-financial companies assets

It is easy to notice that the value of the spillover probabilities deceased significantly from Table 4 to Table 8. The contagion effect of the shadow banks is barley perceivable. Only single asset pairs that contain company (ABC) make exception and illustrate a noticeable spillover probability. This can be traced back to the worldwide economy recession. Toward end of 2008 a series of companies went in bankruptcy and the survived enterprises also experienced significant loss. Indeed AmerisourceBergen Corporation is one of the companies which were strongly affected by the real economic downturn.

Also the liquidity spread contagion likelihood in Table 9 decreased significantly compared to Table 5 and Table 7. Unlike the results displayed in the previous tables, the value of spillover probability is no longer considerably higher than the spillover probability estimated from the asset crash (Table 8). The values between these two tables become rather similar. We believe the reason is that companies had trouble (due to less consumption, export etc.), and not because of the liquidity shortage on the market.

Table 9: Estimated liquidity spread spillover probability across shadow banks(X) and non-financial companies (Y)

Spreads (X-Y)	P {k=2| k ≥1}	P {Y > y| X > x)	P {X > x| Y > y)
HTR - ABT	0.221	0.290	0.581
HTR - ABC	0.339	0.324	0.444
HTR - NS	0.303	0.315	0.443
MRF - ABT	0.218	0.290	0.566
MRF - ABC	0.217	0.342	0.381
MRF - NS	0.303	0.343	0.322
FMY - ABT	0.023	0.025	0.304
FMY - ABC	0.064	0.070	0.204
FMY - NS	0.175	0.535	0.191

Quantile equal x = y = 10%, where X refers to the spread increase of shadow bank assets and Y refers to the spread increase of non-financial companies assets

7. Conclusion

In this paper we considered systemic risk estimation introduced by Straetmans (2000), which is measured as the probability of extreme spillovers within a bivariate extreme value framework. For the extreme link measurement between the tail probabilities, the stable tail dependence function was applied.

We estimated the spillover probabilities between the different financial sectors. In our results, we were able to prove fairly strong extreme interdependencies between shadow banks and the regular banking sector. However, depending on their exposure to the shadow banking assets, banks are unequally affected by the collapse of the shadow banking sector. The outcome indicates that the conditional systemic risk for the regular banking sector decreases when the degree of engagement to the shadow banking sector decreases. Hence, companies in the non-financial sector, which were not directly involved in subprime mortgage instruments and shadow banking, were able to escape from the direct negative impact of the shadow banking crash. Nevertheless, the collapse of the shadow banking sector induced the "domino" effect and spread the crisis to the rest of the economy, where the enterprises were strongly affected in the end.

7.1 Implication for practice

This paper illustrates empirically the extreme link between the shadow banking sector and the regular banking sector. Through the resulting high spillover probability, the paper empirically clarified the importance of this unregulated, but systematically important, *banking sector*. Our results serve as a pre-warning function that sends a clear message to regulators about the potential systemic risk that exists within the financial markets. Basel III requirements are not totally the right answer to the financial crisis. As we know, the crash was originated outside the regulated banking system. Hence, how to regulate the whole financial system, in a way that the systematic risk can be minimized, becomes the next challenge for regulators.

Because no other studies have used measurements like the ones in this paper (measuring the contagion effect of the shadow banking sector), regulators, risk managers, and any other interest groups (eg, investors) could use our results as additional information to define (or adjust) existing regulatory framework, risk-hedging strategies (asset allocation and risk diversification), and portfolio-building approaches.

7.2 Limitations

Shadow banks are not yet regulated and remain "mysterious" and opaque. Therefore, in general, the availability of sufficient data is rather poor. Data, which can be easily obtained from the well-known data providers such as Bloomberg or DataStream, are total return time series. Hence, due to the scarcity of data sources, we were not able to identify a clear shadow bank proxy. We believe, however, that if one is able to collect more precise information, eg which banks are exposed to which shadow banking assets, one can observe an even higher spillover effect. However, risk managers do have access to such information. They could re-perform our estimation process and calculate the customized contagion likelihood. This could help them to better measure the potential risks.

Finally, we also wanted to investigate whether the estimated extreme link between the shadow banking sector and the regular banking sector would change when we go beyond our sample horizon. We wanted to look at the dependencies structure outside the period of extreme events. However, the total time series of many shadow banking assets have a time horizon that is shorter than 25 years. Therefore, this measurement could not be used.

6. Bibliography

Acharya,V.-V., Schnabl, P.,& Suarez, G. (2011). *Securitization without risk transfer*. Found on Augugst 5th, 2012 at Http://ssrn.com/abstract=1364525

Adrian, T. &Ashcraft, A.-B. (2012). *Shadow banking regulation*. Found on December 10th, 2012 at Http://www.newyorkfed.org/research/staff_reports/sr559.html

Adrian, Z., Ashcraft, A., Boesky, H. & Pozsar, Z. (2010). *Federal Reserve Bank of New York Staff Reports: Shadow Banking*. Found on September 12th, 2011 at Http://www.ny.frb.org/research/staff_reports/sr458.pdf

Adrian, T. & Shin, H.-S. (2009). *The shadow banking system: Implication for financial regulation*. Found on December 10th, 2012 on Http://ssrn.com/abstract=1441324

Allen, W, A. & Moessner, R. (2011, July). *The international propagation of the financial crisis of 2008 and a comparison with 1931.* BIS Working Paper Online. Found on October 20th, 2011 at http://www.bis.org/publ/work348.pdf

Basel Committee on Banking Supervision. (2008). *Liquidity Risk: Management and Supervisory Challenges*. Found on October 1st 2011 atHttp://www.bis.org/publ/bcbs136.htm

Basel Committee on Banking Supervision. (2009). *Report on Special Purpose Entities. Found on September 20th 2011 at*Http://www.bis.org/publ/joint23.htm

Basel Committee on Banking Supervision. (2010). *Base III: International framework for liquidity risk measurement, standards and monitoring.* Found on September 27th, 2011 atHttp://www.bis.org/publ/bcbs188.htm

Bensalah, Y. (2000). *Steps in applying extreme value theory to finance: a review.* Found on January 5th, 2013 at Http://www.bankofcanada.ca/wp-content/uploads/2010/01/wp00-20.pdf

Beirlant, J., Vynckier, P., and Teugles, J. (1996). *Tail-index estimation, pareto quantile plots and regression diagnostics.* Journal of the American Statistical Association. 91. 1659-1667.

Bollerslev, T., Engle & Nelson, (1994). *ARCH models: Properties, Estimation and testing*. Journal of Economic Surveys, 7, 350-362.

Borio, C. (2009). BIS Working Papers: *Ten Propositions about liquidity crises.* Found on September 27th, 2011 atHttp://www.bis.org/

Brunnermeier, M. &Pedersen, L. (2009). *Market liquidity and funding liquidity*. Review of Financial Studies 22, 2201–2238.

Cheung, W., Fung, S. & Tsai, S. (2010). *Global capital market interdependence and spillover effect of credit risk: evidence from the 2007-2009 global financial crisis*. Applied Financial Economics, Taylor and Francis Journals, vol. 20(1-2), pp. 85-103.

Covitz, D., Liang, N. & Suarez, G.-A. (2012). *The evolution of a financial crisis: collapse of the asset-backed commercial paper market*. Found on August 5th, 2012 at Http://ssrn.com/abstract=1364576

Danielsson, J., Jorgensen, B.-N, Samorodnitsky, G., Sarma, M. & Vries, C.-G. (2011). *Fat tails, VaR and subadivitity*. Found on Feburary 4th, 2013 at Http://www.riskresearch.org/files/JD-Cd-BJ-SM-GS-35.pdf

Delahaye, P. B. (2011). Base III: *Capital Adequacy and Liquidity after the Financial Crisis*. Found on November 3th, 2011 at http://www.law.harvard.edu/programs/about/pifs/llm/select-papers-from-the-seminar-in-international-finance/llm-papers-2010-2011/delahaye.pdf

Donald, W., K., A. (1991), *Heteroskedasticity and autocorrelation consistent covariance matrix estimation*. Found on Januar 5th, 2013 at Http://www.utdallas.edu/~d.sul/Econo2/andrews91.pdf

Drehmann, M. & Nikolaou, K. (2010). *Funding liquidity risk: definition and measurement.* Found on December 3th, 2012 at http://www.bis.org/search/?sndex=alike&_st=false&c=10&q=liquidity+risk&mp=any&adv=1&sb=0&n=1

Eichengreen, B., Mody, A., Nedeljkovic, M. & Sarno, S. (2009). *How the Subprime Crisis went Global: Evidence From Bank Credit Default Swap Spreads*. Found on November 3th, 2011 at Http://www.nber.org/papers/w14904

Embrechts, P., Frey, R., & McNeil A.-J. (2005) *Quantitative Risk Management: Concept, Techniques and Tools*. Printed in the United States of America.

Embrechts, P., Klüppelberg, C., & Mikosch, T. (1997). *Modeling extremal events for insurance and finance*. Berlin: Springer.

Financial Stability Board. (2011). *Shadow Banking: Scoping the Issues*. Found on November21th, 2011 atHttp://www.financialstabilityboard.org/publications/r_110412a.pdf

Franke, J., Hafener, C., & Härdle, W. (2008) *Statistics of financial markets* (second ed.). Berlin: Springer.

Gennaioli, N., Shleifer, A., & Vishny, R.-W. (2011). *A model of shadow banking*. Found on August 5th, 2012 at Http://www.nber.org/papers/w17115

Gorton, B. G. (2009). *Information, Liquidity and the (ongoing) Panic of 2007.* Found on October 3 th, 2011 atHttp://www.nber.org/papers/w14649

Gorton, B. G. (2008). *The Subprime Panic*. Found on October 3 th, 2011 atHttp://www.nber.org/papers/w14398

Gorton, B.- G. & Metrick. A. (2009). *Securitized banking and the run on repo*. Found on Octorber 24th, 2011 at Http://www.nber.org/papers/w15223

Gorton, B.- G. & Metrick. A. (2010). *Regulating the Shadow Banking System*. Found on Octorber 24th, 2011 at Http://ssrn.com/abstract=1676947

Gorton, B.- G. & Souleles, S. - N. (2005). *Special Purpose Vehicles and Securitization*. Found on September 28th, 2011 atHttp://www.nber.org/papers/w11190

Hsu, J. & Moroz, M. (2010). *Shadow Banks and the Financial Crisis of 2007-2008*. Found on September 28th, 2011 atHttp://ssrn.com/abstract=1574970

Kyle, A., Xiong, W.(2001). *Contagion as a wealth effect*. Journal of Finance 56, 1401–1440.

LeBaron, B. & Samanta, R. (2004). *Extreme value theory and fat markets*. Found on Januar 4th, 2013 at Http://people.brandeis.edu/~blebaron/wps/tails.pdf

Lechner, C. (2009). Ursachen der Krise und offene Themen. In C. Lechner & M. Kreutzer (Eds.), K*onsequenzen aus der Finanzmarktkrise Perspektiven der HSG* (pp. 4-6). St.Gallen: Universität.

Longstaff, F.A. (2010). *The subprime credit crisis and contagion in financial markets.* Journal of Financial Economics, Volume 97, Issue 3, pp. 436-450, September 2010.

McNeil, A. J. (1996). *Estimating the Tails of Loss Severity Distributions using ExtremeValue Theory*. Found on February 6th, 2013 atftp://ftp.math.ethz.ch/users/mcneila/astin.pdf

McNeil, A. J. (1996). *Extreme Value Theory for Risk Managers*. Found on February 6th, 2013 athttp://www.math.ethz.ch/~mcneil/ftp/cad.pdf

Nersisyan, Y. & Wray, L.-R. (2010). *The global financial crisis and the shift to shadow banking*. Found on Juli 13th, 2012 at Http://www.levyinstitute.org/pubs/wp_587.pdf

Ojo, M. (2010). *Financial stability, New Macro Prudential Arrangements and Shadow Banking: Regulatory Arbitrage and Stringent Basel III Regulations.* Found on October 24th, 2011 at Http://ssrn.com/abstract=1859543

Ricks, M. (2010). *Shadow Banking and financial regulation*. Found on December 10th, 2012 on *Http://ssrn.com/abstract=1571290*

Rockafellar, R.-T. & Uryasev, S. (2002). *Conditional value at risk for general loss distributions*. Found on January 3th at http://www.ise.ufl.edu/uryasev/files/2011/11/cvar2_jbf.pdf

Sklar, A. (1959). *Fonctions de r´epartition `a n dimensions et leurs marges.* Publications de l'Institut de Statistique de l'Universit´e de Paris 8, 229-231.

Smith, R. L. (2009). *Extreme Value Theory*. Found on February 6th, 2013 at http://www.unc.edu/~rls/s890/evtclass.pdf

Sorge, M. (2004). *BIS working papers: Stress testing financial system- an overview of current methodologies*. Found on September 12th, 2012 athttp://www.bis.org

Straetmans, S. (2000). *Extremal spillovers in financial markets.* Serie Research Memoranda 0013, VU University Amsterdam, Faculty of Economics, Business Administration and Econometrics.

Tarullo, D.-K. (2012). *Shadow banking after the financial crisis*. Found on December 10th 2012 at http://www.bis.org/review/r120614i.pdf?frames=0

Tian, J. B. (2010). *Shadow Banking System, Derivatives and Liquidity Risks*. Found on September 12th 2011 atHttp://ssrn.com/abstract=1571707

Vayanos, D. (2004). *Flight to quality, flight to liquidity, and the pricing risk*. Found on December 2th, 2012 at Http://papers.ssrn.com/sol3/papers.cfm?abstract_id=509858

Wingnall, B. A. & Atkinson, P. (2010). *Thinking Beyond Basel III: Necessary solutions for capital and liquidity.* Found on November21th, 2011 at OECD Journal: Financial Market Trends, Volume 2010-Issue 1

Yakov, A., (1986), *Asset pricing and the bid-ask spread*. Journal of Financial enconomics, 17, 223-249.

Yamai, Y. & Toshinao, Y (2005), *Value-at-risk versus expected shortfall: A practical perspective*. Journal of banking and Finance, 29, 997-1015

Yi, X. R. & Wang. G. G. (2010). *Financial Analysis of U.S. Sub-prime liquidity crisis transmission mechanism*. Found on September 12th, 2011 athttp://www.cqvip.com/qk/97926x/201005/34471697.html.